An empirical note on the long-run effects of public and private RD on TFP

Herzer, Dierk

29 May 2020

An empirical note on the long-run effects of public and private R&D on TFP

Dierk Herzer*

Department of Economics, Helmut-Schmidt-University Hamburg, Holstenhofweg 85, 22043 Hamburg, Germany

ABSTRACT

Several studies have examined the long-run effects of public and private R&D on TFP with mixed results. A common feature of these studies is the use of stocks of public and private R&D capital, constructed under the implicit assumption that the prices of GDP, public R&D, and private R&D move identically. Thus, the results of these studies may be biased to the extent that this assumption is violated. The main contribution of this note is to avoid this bias by using numbers of public and private sector researchers to measure R&D activity in the public and private sector. Contrary to previous studies, it is found—using numbers of researchers in the public and private sector—that there is strong evidence of a significant positive long-run effect of both public and private R&D on TFP and of a greater effect of public R&D than private R&D. Consistent with the mixed evidence reported in the literature, it is also found that the use of public and private R&D stocks produces mixed results regarding the long-run effects of public and private R&D on TFP.

JEL classification:

O30, O47, O11

Keywords:

public R&D, private R&D, total factor productivity, panel cointegration

* *E-mail address:* herzer@hsu-hh.de

1. Introduction

Although industrial firms perform the bulk of applied research and development (R&D) that is necessary before introducing new products to the marketplace, the increase in academic patenting since the 1980s documents that researchers in universities and other public research organizations engage in applied commercial research and thereby directly contribute to the stock of applied technical knowledge—like their counterparts in industry. In addition, university researchers and other public scientists engage in basic scientific research. To the extent that basic scientific research in universities and other public research organizations enhances the productivity of applied R&D in industry, public R&D should also have an indirect effect on the stock of applied technical knowledge. Thus, one would expect to find that both public and private R&D increase total factor productivity (TFP), with a larger long-run elasticity for public than private R&D. The evidence to support this expectation is, however, far from conclusive.

Guellec and van Pottelsberghe de la Potterie (2004), using a panel of 16 OECD countries over the period 1980-1998, and Luintel et al. (2014), employing panel data for 16 OECD countries over the period 1982-2004, find a significant positive long-run effect of both private R&D and public R&D on TFP, but their results provide no clear evidence of a greater effect of public R&D. Soete et al. (2020) find, using time series data for the Netherlands over the period 1968-2014, that both private and public R&D activities have a significant positive long-run effect on TFP and that the long-run elasticity for private R&D is larger than the long-run elasticity for public R&D. Bengoa et al. (2017), using a panel of 17 Spanish regions over the period 1980-2007, and Voutsinas and Tsamadias (2014), employing time series data for Greece for the period 1981-2007, detect a significant long-run effect only for public R&D. Coe et al. (2009) find, based on regressions for a 24-country OECD panel for the period 1971-2004, that private R&D is significant and positive, while public R&D is not robustly significant. In a panel study of 20 OECD countries for the period 1971-2002, van Elk et al. (2019) report consistently positive results for private R&D, but mixed results for public R&D, ranging from significant negative to significant positive associations. Finally, Erken et al.'s (2009) panel study of 20 OECD countries over the period 1971-2002 shows a significant positive long-run relationship between private R&D and TFP and a significant negative long-run relationship between public R&D and TFP.[1]

In view of these mixed findings, it is by no means clear how public and private R&D affect TFP, and further evidence is needed to clarify the long-run effects of public and private R&D on TFP. The purpose of this note is to provide further evidence on this issue, using an alternative measure of public/private R&D activity—the number of researchers in the public/private sector.

To measure public and private R&D, all of the above TFP studies use real stocks of public and private R&D capital, constructed from deflated public and private R&D expenditure data based on the GDP deflator. The R&D data underlying these studies are thus based on the assumption of identical price deflators for GDP, public R&D expenditures, and private R&D expenditures. Since this assumption is likely to be seriously violated in several years,[2] changes in public and private R&D expenditures/stocks may, in part, reflect measurement error rather than real changes in public and private R&D activity, and this measurement error may lead to biased estimates of the long-run elasticities of TFP with respect to public and private R&D. Thus, it is possible that some of the conflicting findings in the literature reflect biases associated with the use of stocks of public and private R&D capital and that the use of numbers of researchers in the public and private sectors generates more intuitively plausible results than the use of stocks of capital in the public and private sectors; the advantage of using the number of public/private sector researchers is that this measure does not depend on prices, and is thus more likely to reflect real public/private R&D activity.

The primary contribution of this note is to reexamine the long-run effects of public and private R&D on TFP using numbers of public and private researchers as measures of public and private R&D activity. Additional contributions of this note are as follows: First, we present a simple theoretical model to formalize the intuition of how public and private R&D can be expected to

---

[1] Three other related studies should be mentioned. Lichtenberg (1992) finds that private R&D investment (measured as a percentage of GNP) is positive and significant in cross-country regressions for a sample of 53 countries for the (log) level of GDP per adult in 1985 and GDP per adult growth in the period 1960-1985, while public R&D investment is insignificant or even negative. Park (1995) examines the relationship between the growth rates of public and private R&D capital per hour and the growth rate of growth rate of output per hour using panel data for 10 OECD countries over the period 1973-1987. He finds a positive and significant relationship between the growth rate of private R&D capital per hour and the growth rate of growth rate of output per hour; the growth rate of public R&D capital per hour is significantly positive only when the growth rate of private R&D capita is not included in the model (i.e., when the growth rate of private R&D capita is included, the growth rate of public R&D capital becomes insignificant). Bassanini and Scarpetta (2001) examine the long-run effects of public and private R&D expenditures (measured as percentages of GDP) on GDP per capita in a panel of 15 OECD countries between 1971 and 1998 and find a positive effect for private R&D expenditures and a negative effect for public R&D expenditures. Since these studies account for physical and human capital in explaining labor productivity (growth), they indirectly capture the effects of (growth in) public and private R&D on TFP (growth).

[2] Two well-known facts are: (1) more than half of R&D expenditures are labor costs (see, e.g., Becker, 2015); (2) the growth rate of salaries of researchers in the public sector differs (sometimes substantially) from the growth rate of salaries of researchers in the private sector (see, e.g., Hansen and Guidugli, 1990). These facts indicate that it is problematic to assume identical price deflators for public and private R&D expenditures (or to use shares of public and private R&D expenditures in GDP as measures of the shares of public and private R&D activities in total economic activity).

affect TFP. The model also helps justify the empirical specification and, more specifically, the use of numbers of public and private researchers for empirically examining the long-run effects of public and private R&D on TFP. Second, we also use stocks of public and private R&D expenditures to estimate the long-run elasticities of TFP with respect to public and private R&D and to compare the estimates based on the stocks with those obtained from using the numbers. Third, we use data for a more recent period than other studies, thus updating previous results. Fourth, we employ both traditional and more recent panel cointegration methods.

The structure of this note is as follows. Section 2 introduces the theoretical framework. Section 3 discusses the econometric specification and the data. Section 4 presents the empirical results, and Section 5 presents the conclusions.

2. Theoretical framework

Suppose that total output of country i at time t, Y_{it}, is given by a Cobb-Douglas production

$$Y_{it}=A_{Tit}K_{it}^{\alpha}(L_{it}n_{it}h_{it})^{1-\alpha}, \quad 0 < \alpha < 1, \tag{1}$$

where K_{it} denotes the stock of physical capital, α is the elasticity of output with respect to capital, L_{it} is the number of workers, n_{it} and h_{it} represent hours and human capital per worker, respectively, $1–\alpha$ is the elasticity of output with respect to human capital augmented labor, and A_{Tit} is the stock of applied technical knowledge relevant to the development of new and better products and production processes, measured by TFP.

The empirical literature generally specifies TFP as an ad hoc function of the multiplicative form

$$A_{Tit}=c_i PRS_{it}^{\varphi}\, PUS_{it}^{\psi} e_{it} \tag{2}$$

where c_i is a country-specific constant, PRS_{it} is the private R&D capital stock, PUS_{it} is the public R&D capital stock, and e_{it} represents all other factors that determine the level of TFP. As is well known, φ and ψ can be interpreted as the long-run elasticities of TFP with respect to PRS_{it} and PUS_{it}, respectively, if the logs of the variables in equation (2) are non-stationary and cointegrated.

Equation (2) can also be derived formally from two knowledge production functions: a production function for applied technical knowledge,

$$\dot{A}_{Tit} = \delta_{Ti}\, PR_{it}^{\lambda}\, PU_{it}^{\lambda}\, A_{Tit}^{\phi}\, A_{Sit}^{\beta}$$

(3)

and a production function for basic scientific knowledge,

$$\dot{A}_{Sit} = \delta_{Si} PU_{it}^{\gamma}\, A_{Sit}^{\phi}$$

(4)

where $\dot{A}_{Tit}$ represents the flow of new applied technical knowledge, $\dot{A}_{Sit}$ is the flow of new basic scientific knowledge, A_{Sit} denotes the stock of basic scientific knowledge, δ_{Ti} and δ_{Si} are constants of proportionality, PR_{it} is private research effort, and PU_{it} stands for public research effort.

Equation (3) is based on the fact (mentioned in the introduction) that researchers in both industry and public organizations engage in applied commercial research and therefore assumes that the emergence of new technological knowledge depends on research effort in industry and in the public sector. PR_{it} enters the equation multiplicatively with PU_{it}, which can be justified by university-industry interactions in the innovation process (so that neither private nor public research substitutes perfectly for the other). In addition, equation (3) assumes that the emergence of new technological knowledge depends on both the stock of technological knowledge and the stock of scientific knowledge. In contrast, equation (4) assumes that new basic scientific knowledge is only a function of research effort of universities and other public research organizations and of the existing stock of scientific knowledge.

The parameters λ and γ, where $0 < \lambda \leq 1$ and $0 < \gamma \leq 1$, capture the possibility of duplication in research (i.e., the possibility that doubling the number of researchers less than doubles the production of new knowledge because of duplication). For simplicity, we assume the same duplication parameter for public and private research effort in equation (3), although it could be that there is less duplication of research effort in the public research sector, since universities might have less incentive to try to keep research secret.

Similarly, it is assumed that the ϕ parameter is the same for the technical knowledge stock and its scientific counterpart and thus that the magnitude of the (positive or negative) externality in the production of new technical knowledge from the stock of technical knowledge is equal to the magnitude of the externality in the production of new scientific knowledge from the stock of scientific knowledge. Following Jones (1995), we impose $\phi < 1$ so that technical/scientific ideas still become either easier ($\phi > 0$) or harder ($\phi < 0$) to find as the stock of technical/scientific ideas increases.

Finally, β parameterizes the extent to which the productivity of applied technical research depends upon the stock of basic scientific knowledge. A priori, we expect $\beta > 0$.

Rewriting equations (3) and (4) as

$$\frac{\dot{A}_{Tit}}{A_{Tit}} = \delta_{Ti}\, PR_{it}^{\lambda}\, PU_{it}^{\lambda}\, A_{Tit}^{\phi-1}\, A_{Sit}^{\beta} \tag{5}$$

and

$$\frac{\dot{A}_{Sit}}{A_{Sit}} = \delta_{Si} PU_{it}^{\gamma}\, A_{Sit}^{\phi-1} \tag{6}$$

and assuming that both stocks grow at a constant rates in the long run (which is a reasonable assumption given that the growth rate of TFP is typically found to be stationary), the above equations can be solved for the stock of technical knowledge and the stock of scientific knowledge, respectively,

$$A_{Tit} = \left(\frac{\delta_{Ti}}{g_{Ti}}\right)^{\frac{1}{1-\phi}} PR_{it}^{\frac{\lambda}{1-\phi}}\, PU_{it}^{\frac{\lambda}{1-\phi}}\, A_{Sit}^{\beta} \tag{7}$$

$$A_{Sit} = \left(\frac{\delta_{Si}}{g_{Si}}\right)^{\frac{1}{1-\phi}} PU_{it}^{\frac{\gamma}{1-\phi}} \tag{8}$$

where $g_{Ti} \equiv \frac{\dot{A}_{Tit}}{A_{Tit}}$ and $g_{Si} \equiv \frac{\dot{A}_{Sit}}{A_{Sit}}$ represent the constant growth rate of technical knowledge and the constant growth rate of scientific knowledge, respectively. Substituting (8) into (7) and adding e_{it} yields the equation that corresponds to equation (2) when the public/private R&D capital stock is used as a measure of public/private research effort:

$$A_{Tit} = c_i PR_{it}^{\varphi}\, PU_{it}^{\psi} e_{it} \tag{9}$$

where $c_i \equiv \left(\frac{\delta_{Ti}}{g_{Ti}}\right)^{\frac{1}{1-\phi}} \left(\frac{\delta_{Si}}{g_{Si}}\right)^{\frac{\beta}{1-\phi}}$, $\varphi \equiv \frac{\lambda}{1-\phi}$, and $\psi \equiv \frac{\lambda}{1-\phi} + \frac{\gamma\beta}{1-\phi}$.

Thus, since the number of researchers is also a commonly used measure of research effort, our simple theoretical framework justifies the use of the number researchers in the private sector, PRR_{it}, and the number researchers in the public sector, PUR_{it}, for examining the long-run effects of private and public R&D on TFP. In addition, since it is reasonable to assume that opportunities for commercial technological innovation are contingent on the stock of basic scientific knowledge, and thus that β is positive, our theoretical framework not only predicts that both the long-run elasticity of TFP with respect to private R&D effort and the long-run elasticity of TFP with respect to public R&D effort should be positive, but also that the latter should be greater than the former.

3. Econometric specification and data

Taking logs of equation (9) yields the equation that is the basis for our empirical analysis:

$$\log A_{Tit} = c_i + \varphi \log PR_{it} + \psi \log PU_{it} + \vartheta F_t + \varepsilon_{it} \tag{10}$$

where $\vartheta F_t + \varepsilon_{it} \equiv \log e_{it}$, and the process F_t represents unobserved common factors (such as global technological progress and global crises) that, if not controlled, can induce cross-sectional error dependence and lead to inconsistent estimates.

Following common practice, we calculate A_{Tit} as the residual from the production function (1), assuming α = 1/3. All data used to calculate TFP are from the Penn World Tables (PWT) version 9.1 (available at https://www.rug.nl/ggdc/productivity/pwt/).[3]

The source of our R&D data is the OECD Main Science and Technology Indicators (MSTI) database (available at https://stats.oecd.org/Index.aspx?DataSetCode=MSTI_PUB#). Our first measure of private (public) research effort, the stock of private (public) R&D capital, is constructed from R&D expenditures by the business sector (government and the higher education sectors) in constant dollars using the perpetual inventory equation $S_{it} = E_{it} + (1 - \delta)S_{it-1}$,[4] where S_{it} is the stock of R&D expenditures, E_{it} denotes R&D expenditures, and δ is the depreciation rate. Consistent with the literature, we set the initial value of the R&D stock equal to $E_{i0}/(g + \delta)$, where E_{i0} is the value of the expenditure series the first year it is available, and g is the average growth rate of expenditures over the estimation period. Following the literature, we use a depreciation rate of δ = 15%.

Our second and primary measure of PR_{it} (PU_{it}), the number of researches in the private (public) sector, is defined as the number of full-time equivalent researchers in the business sector

[3] The Penn World Tables 9.0 contains its own measure of TFP, which is based on a translog production function in which the labor share varies across countries and across time. However, as argued by Jones (2016), such a measure isproblematic because it implies that countries and years with the same inputs and the same level of TFP will have different outputs. In fact, it is still debated whether the labor share is approximately constant across time and space (with a value of about 2/3). While Karabarbounis and Neiman (2014) document a secular decline in the labor share in most advanced countries since the early 1980s, Cette et al. (2020) challenge this finding and demonstrate that, when corrected for measurement error, the labor share of advanced economies does not follow a secular trend. Therefore, we follow the common practice of assuming α = 1/3.

[4] The existing official OECD estimates of real R&D expenditures are based on the GDP deflator.

(government and the higher education sectors).[5] To ensure consistency, we use a common sample for both measures.

Given that the MSTI data start in 1981 and end in 2017, the sample covers the period between 1981 and 2017. We include all countries with complete time series and at least 20 time-series observations, resulting in an unbalanced panel of 577 observations from 20 OECD countries (Belgium, Canada, Czech Republic, France, Germany, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, South Korea, Spain, Turkey, and the United Kingdom).[6]

4. Empirical results

Equation (10) assumes that, in the long-run, permanent changes in $\log PR_{it}$ and $\log PU_{it}$ are associated with permanent changes in $\log A_{Tit}$. Empirically, this implies that when $\log PR_{it}$, $\log PU_{it}$, and $\log A_{Tit}$ are stochastically non-stationary, these variables must be cointegrated for our model to be valid; if $\log PR_{it}$, $\log PU_{it}$, and $\log A_{Tit}$ are non-stationary and not cointegrated, then equation (10) is a spurious regression.[7]

We examine the (non-)stationarity of the variables by testing for unit roots using the procedures suggested by Im et al. (2003) and Pesaran (2007). Given that the standard Im et al. (2003) test, which assumes cross-sectionally independent residuals, suffers from size distortions in the presence of error cross-sectional dependence, we apply this test to demeaned data $x_{it} - N^{-1}\sum_{i=1}^{N} x_{it}$ in place of the original data x_{it}.[8] The Pesaran (2007) test, which accounts for potential error cross-sectional dependence, is applied to the raw data. The results of these tests are reported in Table 1. Both panel unit root tests show that all variables are stochastically non-stationary.

Table 2 presents the results of several tests for panel cointegration between $\log A_{Tit}$, $\log PRS_{it}$ ($\log PRR_{it}$), and $\log PUS_{it}$ ($\log PUR_{it}$). For the tests that assume error cross-sectional independence, such as the Pedroni (1999) and Westerlund (2005) tests, we report results based on demeaned data. For the tests that account for error cross-sectional dependence, such as the Gengenbach et al. (2016) tests, we report results based on the raw data. In sum, these tests suggest that there is a long-run

[5] The total number of researchers is the sum of the number of researchers in four sectors: business, government, higher education, and the private non-profit sector. Due to the lack of data on the number of higher education researchers for the period 1999-2004 for the UK, we construct the number of UK researches in the public sector for this period by subtracting the number of business researchers from the total number of researchers; this should not be a problem since the number of UK researchers in the private non-profit sector is very small or even zero (in 1998, for example).

[6] It should perhaps be noted explicitly that sufficiently long time series on the number of business, government, and higher education researchers are not available for the United States from the MSTI, so that we are forced to exclude the United States from our sample.

[7] As shown by Kao (1999), the tendency for spuriously indicating a relationship may even be stronger in panel data regressions than in pure time-series regressions.

[8] The use of demeaned data is equivalent to using the residuals from regressions of each variable on time dummies and serves to account for potential error cross-sectional dependence.

relationship between logA_{Tit}, logPRS_{it}, and logPUS_{it} and a long-run relationship between logA_{Tit}, logPRR_{it}, and logPUR_{it}, though the evidence is stronger for the latter.

To estimate the long-run elasticities of TFP with respect to private and public R&D based both on the stocks of private and public R&D capital and on the numbers of private and public researchers, we use four different estimators: the panel DOLS (PDOLS) estimator of Kao and Chiang (2000), the group-mean panel DOLS (GMDOLS) estimator suggested by Pedroni (2001), the pooled mean-group (PMG) estimator of Pesaran et al. (1999), and the cross-sectionally augmented distributed lag mean-group (CSDLMG) estimator recently proposed by Chudik et al. (2016). The PDOLS, GMDOLS, and PMG estimators are based on the assumption of error cross-sectional independence and are therefore applied to demeaned data. The CSDLMG estimator, which accounts for potential error cross-sectional dependence, is applied to the raw data.

Table 3 depicts the results of these estimation procedures. The results based on R&D stocks are contradictory, and none of the methods produce significant positive coefficients on both logPRS_{it} and logPUS_{it}.[9] In contrast, the results based on numbers of researchers are similar and consistent with our theoretical expectations. The coefficients on both logPRR_{it} and logPUR_{it} are significant and positive across all four regressions, and the coefficient on logPUR_{it} is always larger than the coefficient on logPRR_{it}.

5. Conclusions

We conclude that the use of numbers of public and private sector researchers generates more plausible estimates of the long-run elasticities of TFP with respect to public and private R&D than the common use of stocks of public and private R&D capital. Consistent with prior literature, we find mixed results regarding the long-run effects of public and private R&D on TFP using public and private R&D stocks. However, using numbers of public and private sector researchers, we find—contrary to previous work, but consistent with our theoretical expectations—that there is strong evidence that both public and private R&D contribute to TFP and that the elasticity of TFP with respect to public R&D is larger than the elasticity of TFP with respect to private R&D.

References

Bassanini, A., Scarpetta, S., Hemmings, P., 2001. The driving forces of economic growth: panel data evidence for the OECD countries. *OECD Economic Studies*, 33, 9-56.

Becker, B., 2015. Public R&D policies and private R&D investment: A survey of the empirical evidence. *Journal of Economic Surveys*, 29, 917-942.

[9] It should perhaps be noted that the GMDOLS elasticity for PRS_{it} is positive, but its t-statistic is negative.

Bengoa, M., Martínez-San Román, V., Pérez, P., 2017. Do R&D activities matter for productivity? A regional spatial approach assessing the role of human and social capital. *Economic Modelling*, 60, 448-461.

Bernard, A., Jones, C., 1996. Comparing apples to oranges: Productivity convergence and measurement across industries and countries. *American Economic Review*, 86, 1216-38.

Chudik, A., Mohaddes K., Pesaran, M.H., & Raissi M., 2016. Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. *Advances in Econometrics*, 36, 85-135.

Cette, G., Koehl, L., Philippon, T., 2020. Labor share. *Economics Letters*, 188, 108979

Coe, D.T., Helpman, E., Hoffmaister, A.W., 2009. International R&D spillovers and institutions. *European Economic Review*, 53, 723-741.

Erken, H., Donselaar, P., Thurik, R., 2009. Total factor productivity and the role of entrepreneurship. Tinbergen Institute Discussion Paper 2009-034/3.

Gengenbach, C., Urbain, J.-P., Westerlund, J., 2016. Error correction testing in panels with common stochastic trends. *Journal of Applied Econometrics*, 31, 982-1004.

Guellec, D., Van Pottelsberghe de la Potterie, B., 2004. From R&D to productivity growth: Do the institutional settings and the source of funds of R&D matter? *Oxford Bulletin of Economics and Statistics*, 66, 353-378.

Hansen, W.L., Guidugli, T.F., 1990. Comparing salary and employment gains for higher education administrators and faculty members. *Journal of Higher Education*, 61, 142-159.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115, 53-74.

Jones, C.I., 1995. R&D-based models of economic growth. *Journal of Political Economy*, 103, 759-784.

Kao, C., 1999. Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90, 1-44.

Kao, C., Chiang, M., 2000. On the estimation and inference of a cointegrated regression in panel data. *Advances in Econometrics*, 15, 179-222.

Karabarbounis, L., Neiman, B., 2014. The global decline of the labor share. *Quarterly Journal of Economics*, 129, 61-103.

Lichtenberg, F., 1993. R&D investment and international productivity differences. NBER Working Paper No. 4161, National Bureau of Economic Research, Cambridge, MA.

Luintel, K.B., Khan, M., Theodoridis, K., 2014. On the robustness of R&D. *Journal of Productivity Analysis*, 42, 137-155.

Park, W.G., International R&D spillovers and OECD economic growth. *Economic Inquiry*, 33, 571-591.

Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, 61, 653-670.

Pedroni, P., 2001. Purchasing power parity tests in cointegrated panels. *Review of Economics and Statistics*, 83, 727-731.

Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265-312.

Pesaran, M.H., Shin, Y., Smith, R.P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94, 621-634.

Soete, L.L.G, Verspagen, B., Ziesemer, T.H.W. The productivity effect of public R&D in the Netherlands. *Economics of Innovation and New Technology*, 29, 31-47.

van Elk, R., ter Weel, B., van der Weil, K., Wouterse, B., 2019. Estimating the returns to public R&D investments: Evidence from production function models. *De Economist*, 167, 45-87.

Voutsinas, I., Tsamadias, C., 2014. Does research and development capital affect total factor productivity? Evidence from Greece. *Economics of Innovation and New Technology*, 23, 631-651.

Westerlund, J., 2005. New simple tests for panel cointegration. *Econometric Reviews*, 24, 297-316.

Table 1 Panel unit root tests

	Im et al. (2003)	Pesaran (2007)
logA_{Tit}	0.433	0.282
logPRS_{it}	0.108	0.937
logPUS_{it}	0.943	0.763
logPRR_{it}	0.523	0.755
logPUR_{it}	0.828	0.763

Notes: Reported values are *p*-values. To account for potential error cross-sectional dependence in the Im et al. (2003) test, we used demeaned data. The Pesaran (2007) test accounts for error cross-sectional dependence via the use of (weighted) cross-sectional averages. Two lags were used in the tests. Both tests include country specific intercepts. *** (**) indicate significance at the 1% (5%) level.

Table 2 Panel cointegration tests

	Tests for cointegration between logA_{Tit}, logPRS_{it}, and logPUS_{it}		
	Pedroni (1999)	Westerlund (2005)	Gengenbach et al. (2016)
Panel PP *t*-statistic	-3.134***		
Panel ADF *t*-statistic	-1.099		
Group mean PP *t*-statistic	-3.250***		
Group mean ADF *t*-statistic	-0.996		
Panel variance ratio statistic		-2.302**	
Group mean variance ratio statistic		-3.362***	
ECM *t*-statistic			-4.260***
ECM Wald statistic			23.377***
	Tests for cointegration between logA_{Tit}, logPRR_{it}, and logPUR_{it}		
	Pedroni (1999)	Westerlund (2005)	Gengenbach et al. (2016)
Panel PP *t*-statistic	-2.872***		
Panel ADF *t*-statistic	-2.087**		
Group mean PP *t*-statistic	-4.402***		
Group mean ADF *t*-statistic	-3.473***		
Panel variance ratio statistic		-1.407*	
Group mean variance ratio statistic		-2.368***	
ECM *t*-statistic			-4.163***
ECM Wald statistic			26.7134***

Notes: The dependent variable in the Pedroni (1999) and Westerlund (2005) tests is logA_{Tit}; the dependent variable in the tests of Gengenbach et al. (2016) is ΔlogA_{Tit}. For the Pedroni (1999) tests, the lag length was chosen using the modified Schwarz criterion, with a maximum of four lags allowed. For the Gengenbach et al. (2016) test, we used the general-to-specific procedure; we started with a lag length of one (longer lags were not feasible given the limited number of time-series observations available (for some countries) here), and then all insignificant first differences according to individual *t*-tests were eliminated to obtain more efficient estimates of the coefficients of the level variables. The critical values for the Gengenbach et al. (2016) *t*-test/Wald test (for $N = 20$) are as follows: -3.396/16.077 (1% level), -3.003/15.137 (5% level), -2.948/14.587 (10% level). To account for error cross-sectional dependence (due to possible non-stationary common factors), the results of the Pedroni (1999) and Westerlund (2005) tests are based on demeaned data. The Gengenbach et al. (2016) test accounts for error cross-sectional dependence via the use of cross-sectional averages. *** (**) [*] indicate significance at the 1% (5%) [10%] level.

Table 3 Estimates of the long-run relationship between TFP, private R&D, and public R&D

	Results based on R&D capital stocks				Results based on number of researchers			
	PDOLS estimator	GMDOLS estimator	PMG estimator	CSDLMG Estimator	PDOLS estimator	GMDOLS Estimator	PMG estimator	CSDLMG estimator
logPRS_{it}	0.091***	0.040	0.240***	0.237				
	(0.030)	[-2.302]	(0.023)	(0.145)				
logPUS_{it}	0.039	0.146***	-0.175***	0.088				
	(0.040)	[11.75]	(0.033)	(0.148)				
logPRR_{it}					0.058***	0.043***	0.054***	0.072**
					(0.020)	[9.243]	(0.007)	(0.029)
logPUR_{it}					0.061*	0.098***	0.206***	0.142***
					(0.034)	[13.44]	(0.011)	(0.054)
Number of obs.	517	517	497	517	517	517	497	517

Notes: The dependent variable in the PDOLS, MGDOLS, and CSDLMG regressions is logA_{Tit}; the dependent variable in the PMG regressions is ΔlogA_{Tit}. All regressions include country fixed effects. The DOLS regressions were estimated with one lead and one lag. The lag order in the PMG regressions was chosen using the Akaike criterion, with a maximum of four lags allowed. The DOLS and PMG regressions were performed using demeaned data to account for potential error cross-sectional dependence; the CSDLMG estimator controls for potential error cross-sectional dependence via the use of (weighted) cross-sectional averages; the CSDLMG results are based on a specification with three lags of the cross-sectional averages of the explanatory variables (and one lag of the first differences). Heteroskedasticity and autocorrelation consistent standard errors are in parentheses; the CSDLMG standard errors are also robust to general forms of spatial and temporal dependence. The group-mean DOLS procedure does not yield standard errors of the parameters. For this estimator, we therefore report the associated group mean *t*-statistics (in brackets). *** (**) [*] indicate significance at the 1% (5%) [10%] level.